www.editada.org

International Journal of Combinatorial Optimization Problems and Informatics, 14(1), Jan-April 2023, 86-94. ISSN: 2007-1558.

Deep Learning for greenhouse internal temperature forecast

Juan M. Esparza-Gómez[1] , Héctor A. Guerrero-Osuna[2], Gerardo Ornelas-Vargas[2]
and Luis F. Luque-Vega[3]

[1] Posgrado en Ingeniería y Tecnología Aplicada, Universidad Autónoma de Zacatecas, Zacatecas 98000, México.
[2] Universidad Politécnica del Sur de Zacatecas, Juchipila, Zacatecas 99970, México
[3] Centro de Investigación, Innovación y Desarrollo Tecnológico CIIDETEC-UVM, Universidad del Valle de México, 45601, Zapopan, Jalisco, México;
juan.esparza@upsz.edu.mx
hectorguerreroo@uaz.edu.mx
ornelashlls@gmail.com
luis.luque@uvmnet.edu

Abstract. The microclimate inside a greenhouse forecast has been a case of study in recent years; an adequate forecast of variables such as internal temperature helps farmers prevent losses in the harvest. In this investigation, the forecast of the greenhouse internal temperature is implemented through Recurrent Neural Networks (RNN) topology with Long-Short Term Memory (LSTM) algorithm. The analysis is performed with the many to one configuration for a sequence of three input elements and one output element for each of the year's four seasons. The metrics used for the analysis and validation of the data were the RMSE, MAE, R2, and Ceff. These metrics provide the level of efficiency and goodness of the RNN-LSTM showing how the variables considered provide significance to the forecast of one hour into the future of the internal temperature. It is shown that the LSTM algorithm within the RNN is an effective tool for a good internal temperature forecast in time series for each season, significantly helping the forecast of climatic variables inside a greenhouse.

Keywords: RNN-LSTM, Temperature prediction, Deep Learning.

Article Info
Received September 21, 2022
Accepted Jan 25, 2023

1 Introduction

Recently, the time series prediction model has been actively used in several fields, including attempts to develop prediction models for greenhouses [1]; techniques such as computational fluid dynamics (CFD) have been applied focused on real-time monitoring implemented in Matlab [2]; wireless sensor network systems for data monitoring and use with LSTM algorithm [3]; and Backpropagation Multilayer algorithms (BP-ML) [4].

Other forecasting systems used inside greenhouses have been models using empirical composition in conjunction with LSTM algorithms (EEMD-LSTM) [5]. In [6], models based on Recurrent Neural Networks (RNN) and in [7] RNN with Long-Short Term Memory (RNN-LSTM) algorithms are proposed.

The main components of an LSTM network are a sequence input layer and an LSTM layer. A sequence input layer inputs the sequence or time-series data onto the network. An LSTM layer learns long-term dependencies between sequence data time steps [8-10]. Thus, the RNN model is used to carry out forecasting work from time series. In [1] and [11], RNNs based on an Elman structure were used to simulate the direct dynamics of greenhouse temperature and hygrometry. However, such studies used the current value of the target parameter as the input variable for the prediction model, making overfitting quite likely [12].

Consequently, RNNs are suitable for sequential data processing tasks, including financial forecasting, natural language processing, and weather forecasting [13-14]. The LSTM algorithm reinforces the RNN, turning it into a powerful tool for solving time series and pattern recognition [1] [7].

In [7] and [15], the efficiency of the suggested model is evaluated using different statistical measures such as the root mean square error (RMSE), mean absolute error (MAE) (also seen in [3] [16]), and the Correlation coefficient (R2) (used also in [17]).

In this study, an approach to forecasting the internal temperature of a greenhouse is developed using external and internal climate data captured in a given period of time by a weather station. An RNN-LSTM has been proposed to forecast climatic conditions within greenhouses. The data set used for this estimation considered environmental variables with a sequential behavior due to their effect on the model convergency over time.

2 Related Work

Numerous investigations have been carried out with the objective of forecasting temperature, humidity, solar radiation, and other variables within protected environments such as greenhouses. All these are in order to determine the growth behavior of the crop [9].

There are several forecasting models. However, in recent years predictors based on Artificial Neural Networks have gained importance due to the range of tools provided by Machine Learning and the structures of algorithms.

Dae-Hyun et. al [9] show comparisons between different structures considering various learning algorithms for the time series prediction. Abdulkarim et.al [11] show the advantage of the RNN, which can feedback the neuron output signal to the same neuron in the next time step.

The metrics usually used to assess LSTM prediction performance are the mean square error (MSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), the square root of the mean square error (RMSE),and the Nash-Sutcliffe coefficient of efficiency (NSCE)[9], [11].

The LSTM algorithm has a significant advantage in expanding the memory capacity of the neural network. This characteristic leads to keeping a vast set of background data as a reference for the forecasting system. Keeping a large amount of data can significantly impact the accuracy of the prediction, reducing the RMSE and MAE to 0.5 and 0.004, respectively [2].

Singh [16] implements the RNN-LSTM to work with time series to forecast the Temperature and Relative Humidity inside a greenhouse. For the temperature model, the metrics implemented for its validation were the MAE, RMSE, and R^2, obtaining MAE values of 0.488 for the temperature forecast, guaranteeing that the reliability of the forecast is within ±1°C. The RMSE obtained is 0.865, and the coefficient of determination R^2

is 0.953, which indicates that the general dispersion is small and does not cause a significant error with the observed temperature.
The RNN-LSTM training datasets can be selected in two ways. One way can be with 90% of the data sequence and the remaining 10% for testing and validation of the network. The other way is with 80% of the data sequence for training and the remaining 20% for network testing and validation. All the data must be normalized [3].

3 METHODOLOGY

The present research work presents new contributions for the modeling of the dynamic system using RNN and Deep Learning, with the use of the Long Short Term Memory (LSTM) algorithm. This type of Recurrent Neural Network was proposed in Hochreiter and Schmidhuber in 1997 [18]. In which a memory cell and input, output vector, and a forget gate were introduced, such networks do not present the leakage gradient problem and can preserve the information for more extended periods [18] [19].

The RNN-LSTM topology is based on a generalization of the feedforward neural network that has internal memory. The RNN is recurring in nature as it performs the same function for each data input (Figure 1) [20], while the output of the current input depends on the last calculation. After the output is produced, it is copied and sent back to the recurring network. It considers the current input and the output calculated for the previous input to make a decision. The ADAM algorithm was adopted to make the calculation of the LSTM network more efficient.
The training set was used to fit the models and predictions corresponding to the validation set, then the mean square error (RMSE) of those predicted values was measured [21].

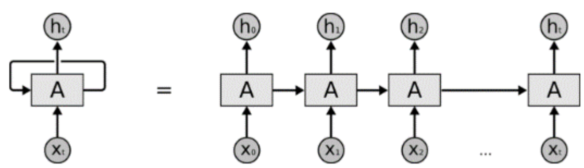

Figure 1. RNN Structure.

Within the RNN-LSTM structure (Figure 2), it first takes X_0 from the input sequence and then generates h_0, which together with X_1 is the input for the next step. So h_0 and X_0 is the input for the next step. Similarly, h_0 of the following is the input with X_2 for the next step, and so on. This way, it keeps remembering the context during training.

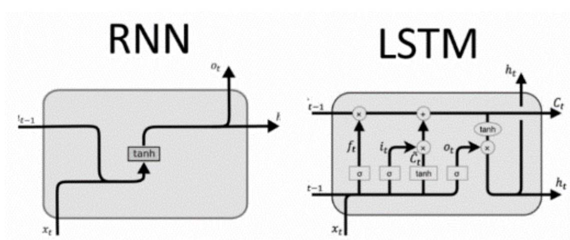

Figure 2. LSTM Structure, Copyright 2020, MathWorks Inc.

The data flow behavior over time t is shown in table 1. It can be seen that the Activation function is a sigmoid function.

Table 1. LSTM structure equations

Nomenclature	*Definition*	*Formula*
i_t	Input Gate	$i_t = \sigma_g(W_i x_t + R_i h_{t-1} + b_i)$
f_t	Forget Gate	$f_t = \sigma_g(W_f x_t + R_f h_{t-1} + b_f)$
g_t	Candidate Gate	$g_t = \sigma_g(W_g x_t + R_g h_{t-1} + b_g)$
o_t	Output Gate	$o_t = \sigma_g(W_o x_t + R_o h_{t-1} + b_o)$

The number of units in the hidden layer will influence the adjustment effect. The batch size must be selected in a way that allows the NN training to converge. Also, if the batch is too large, the required memory will increase significantly [7].

The criteria for evaluating the goodness of the network based on the fit are shown in Table 2 [22].

Table 2. Metrics for the evaluation of the RNN-LSTM

Evaluation	*RMSE*	C_{eff}
Very good	≤ 0.30	≥ 0.91
Good	0.30 – 0.40	0.84 - 0.91
Acceptable	0.40 – 0.50	0.75 - 0.84
Not acceptable	> 0.5	< 0.75

The data collection of the climatic variables was carried out in a greenhouse with a curved roof (165m^2 in area, 27.5m long, 6m wide) located in Mezquitera Sur, at Juchipila, Zacatecas, Mexico. This type of greenhouse is traditionally used without any climate control equipment inside and with natural ventilation.

A Davis Vantage Pro2 meteorological station was used, which monitored internal and external relative humidity and temperature, solar radiation, outdoor temperature, wind direction, wind speed, and time of day. The training and validation were made in a PC with Intel (R) Core (TM) i5-9300H 2.40 GHz quad-core processor with a 16 GB memory. The operating system was Windows 10 64-bit. Matlab software, applying the LSTM Networks library, was used for design.

The data collection was carried out from July 12, 2020, to July 12, 2021, with sampling in 5-minute intervals, which included the parameters of external and internal climatic variables of interest, taking 105,120 samples for training and testing of the RNN-LSTM.

The climatic variables considered in the research work were external temperature (To) in °C, relative humidity (Ho) in %, interior relative humidity (Hi) in %, internal dew point (Di) in %, External solar radiation (Rs) in W/m^2. These climatic variables were selected after a series of trials where the RMSE could be within acceptable values. The climatic variables selected presented a sequenced behavior of the data during periods of 24 hours of observation.

The data were grouped by seasons of the year (summer, autumn, winter, and spring, with 91 days per season) in order to test an RNN-LSTM for each season. The number of combinations tested was obtained from the five variables of interest in arrangements of three input elements. The RNN-LSTM was trained with the 80-20 arrangement, which includes 80% training data and 20% test data. From the 80-20 sequence, the parameters of interest are obtained for their respective analysis based on the results of the training model presented.

The goal is to predict the internal temperature, one hour into the future. The RNN-LSTM structure was defined with 250 hidden layers.

Square Mean Error (RMSE), the Percentage Absolute Mean Error (MAPE), the Determination Coefficient (R^2), and the efficiency Coefficient (Ceff) were used to evaluate the generated RNN-LSTM goodness.

4 Experimental Results

The statistics metrics for the RNN-LSTM goodness achieved for the summer season are shown in Table 3; metrics for autumn are presented in Table 4; Table 5 shows results for winter, and finally, Table 6 presents metrics for spring:

Table 3. Values obtained to determine the efficiency of the RNN-LSTM in the summer season

Input sequence	**RMSE**	**MAE**	$\mathbf{R^2}$	$\mathbf{C_{eff}}$
Hi-Id-To	**0.3333**	**0.0050**	**0.9991**	**0.9991**
Hi-Ho-To	0.9231	0.0194	0.9929	0.9925

Hi-To-Rs	1.4508	0.0361	0.9824	0.9822
Id-Rs-To	1.6820	0.0288	0.9764	0.9737
Ho-To-Rs	3.4302	0.0454	0.9018	0.8830
Hi-Id-Rs	**0.3306**	**0.0046**	**0.9991**	**0.9991**
Hi-Id-Ho	**0.4203**	**0.0062**	**0.9985**	**0.9985**
Hi-Rs-Ho	1.5805	0.0432	0.9792	0.9790
Id-Rs-Ho	1.6487	0.0317	0.9773	0.9749
Id-Ho-To	1.5953	0.0325	0.9788	0.9792

The results found for the autumn season (Table 4) were:

Table 4. Values obtained to determine the efficiency of the RNN-LSTM in the autumn season

Input sequence	**RMSE**	**MAE**	**R^2**	**C_{eff}**
Hi-Id-To	**0.3822**	**0.0090**	**0.9993**	**0.9993**
Hi-Ho-To	1.4106	0.0355	0.9904	0.9912
Hi-To-Rs	5.9674	0.0788	0.8282	0.7461
Id-Rs-To	3.3693	0.0615	0.9452	0.9239
Ho-To-Rs	1.8026	0.0495	0.9843	0.9857
Hi-Id-Rs	**0.3968**	**0.0095**	**0.9992**	**0.9992**
Hi-Id-Ho	**0.3992**	**0.0105**	**0.9990**	**0.9990**
Hi-Rs-Ho	3.4420	0.1764	0.9428	0.9472
Id-Rs-Ho	3.3554	0.0708	0.9457	0.9225
Id-Ho-To	3.3050	0.0677	0.9473	0.9284

The results found for the winter season (Table 5) were:

Table 5. Values obtained to determine the efficiency of the RNN-LSTM in the winter season

Input sequence	**RMSE**	**MAE**	**R2**	**Ceff**
Hi-Id-To	**0.3899**	**0.0103**	**0.9982**	**0.9982**
Hi-Ho-To	1.7979	0.0418	0.9877	0.9889
Hi-To-Rs	2.3246	0.0525	0.9794	0.9758
Id-Rs-To	4.1677	0.0736	0.9338	0.9189
Ho-To-Rs	2.0006	0.0464	0.9848	0.9859
Hi-Id-Rs	**0.3311**	**0.0100**	**0.9974**	**0.9973**
Hi-Id-Ho	**0.3872**	**0.0103**	**0.9981**	**0.9981**
Hi-Rs-Ho	3.5499	0.1386	0.9520	0.9499
Id-Rs-Ho	2.2684	0.0630	0.9804	0.9798
Id-Ho-To	1.7366	0.0550	0.9885	0.9899

The results found for the spring season (Table 6) were:

Table 6. Values obtained to determine the efficiency of the RNN-LSTM in the spring season

Input sequence	**RMSE**	**MAE**	**R2**	**Ceff**
Hi-Id-To	**0.4587**	**0.0119**	**0.9997**	**0.9925**
Hi-Ho-To	3.4945	0.0946	0.9405	0.9340
Hi-To-Rs	2.3948	0.0550	0.9721	0.9742
Id-Rs-To	2.0974	0.0366	0.9786	0.9809
Ho-To-Rs	2.8181	0.0705	0.9613	0.9623
Hi-Id-Rs	**0.6445**	**0.0140**	**0.9970**	**0.9970**
Hi-Id-Ho	**0.6932**	**0.0220**	**0.9952**	**0.9918**
Hi-Rs-Ho	2.7469	0.0659	0.9633	0.9588
Id-Rs-Ho	2.3074	0.0511	0.9741	0.9777
Id-Ho-To	2.8519	0.0550	0.9604	0.9659

From the metrics obtained, it was observed that three of the ten sequences yielded good forecast results of the greenhouse internal temperature. In Table 7, a comparison of statistical meter between this work and others found in the literature for the same application is shown.

Table 7. Comparison of parameters obtained.

Implemented model	RMSE	MAE	R^2	C_{eff}
Hi-Id-To (summer)	0.3333	0.0049	0.9991	0.9991
Hi-Id-Rs (spring)	0.6445	0.0140	0.9970	0.9970
Hi-Id-Ho (spring)	0.6932	0.0220	0.9952	0.9918
[5] (RNN)	1.7963	1.3431	-	-
[5] (LSTM)	1.8044	1.3521	-	-
[5] (EEMD-LSTM)	0.7098	0.5336	-	-
[6] (RNN)	0.865	0.488	0.953	-
[4] (ML-BPP)	0.711	0.558	0.980	-
[2] (CFD)	2.3518	2.0312	-	-

The results of Table 7 show that the model applied with RNN-LSTM is suitable for forecasting the internal temperature one hour ahead. Even when two combinations reach unacceptable RMSE values in the spring season, the Hi-Id-To combination maintains acceptable RMSE results in all four seasons of the year.

Figure 3.a shows the Ti forecast for the Hi-Id-To combination for the summer, and figure 3.b shows the Ti forecast for the Hi-Id-Rs combination in the spring.

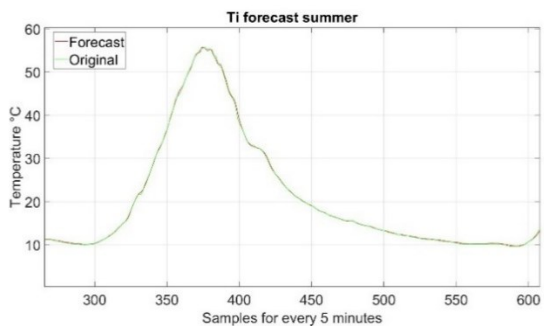

Figure 3.a Ti forecast for the Hi-Id-To combination for the summer.

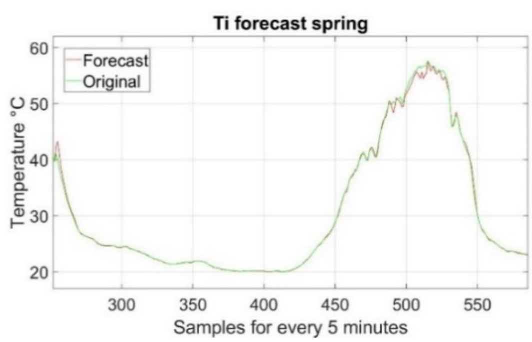

Figure 3.b Ti forecast for the Hi-Id-Rs combination in the spring.

Figure 4.a shows the behavior of RMSE and MAE for the Hi-Id-To combination during the summer season as well as figure 4.b shows the behavior of RMSE and MAE for the same combination within the season of winter.

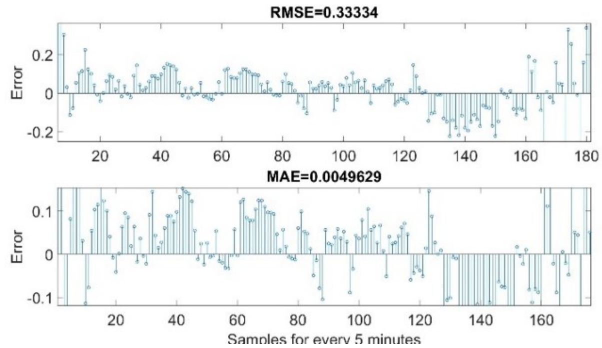

Figure 4.a Behavior of RMSE and MAE for the Hi-Id-To

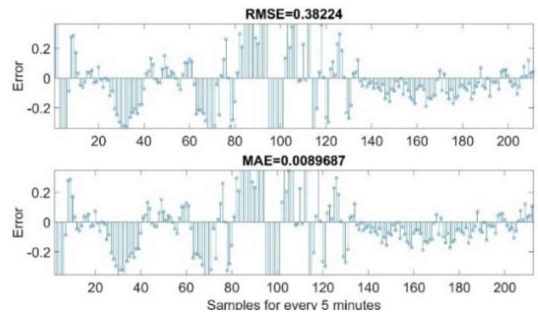

Figure 4.b behavior of RMSE and MAE for the same combination within the season. of winter

Figure 5 shows the behavior of the Ti predicted for a time greater than one hour, this prediction was made for the Hi-Id-To combination in the summer season.

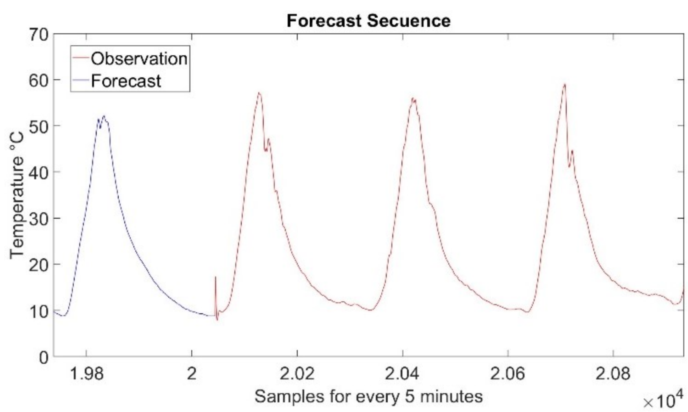

Figure 5. Average forecast sequence.

5 Conclusions and Directions for Further Research

From the results obtained, it is observed that three of the ten of the analyzed combinations present acceptable results, from this it is determined that the combination of Hi-Id-To variables turns out to be effective for the forecast of the internal temperature in the four seasons of the year, reaching values of up to RMSE = 0.3333 and C_{eff} = 0.9991 being acceptable within the validation for the RNN-LSTM, showing that this model is a better predictor compared to techniques such as CFD, EEMD-LSTM and even the RNN or the LSTM algorithm separately, likewise it is observed that the difference between the predicted values and the observed values for Ti is small, this is corroborated by the values obtained by the MAE of up to 0.0049 between forecast and observation. as well as the coefficient of determination R^2 with results of up to 0.9991, this value being an indicator of a good correlation between data, the C_{eff} presents good results as However, the literature shows it;

however, for this study it was not possible to compare it since comparative research was not contemplated or some only estimated the coefficient of relation R^2.

The model applied in this research (RNN-LSTM), shows that, in order to make a forecast with acceptable results, a cycle of 91 days (approximate duration of each season) and samples at intervals of every 5 minutes for the climatic variables of interest, is an appropriate period in the adequate prediction for the internal temperature (Ti) in a greenhouse.

For future work, it is considered to make the comparison of the efficiency against other predictors such as Convolutional Neural Networks with Long-Short Term Memory algorithm (CNN-LSTM), Support Vector Regression (SVR).

References

1. Rodríguez, S.; Gualotuña, T.; Grilo, G., A System for the Monitoring and Predicting of Data in Precision Agriculture in a Rose Greenhouse Based on Wireless Sensor Networks. Procedia Computer Science, 121, 306-313 (2017).
2. Poornima, S.; Pushpalatha, M. Prediction of Rainfall Using Intensified LSTM Based Recurrent Neural Network with Weighted Linear Units. Atmosphere, 10,668, (2019)
3. Xie, A.; Yang, H.; Chen, J.; Sheng, L.; Zhang, Q. A Short-Term Wind Speed Forecasting Model Based on a Multi-Variable Long Short-Term Memory Network. Atmosphere, 12, 651, (2021).
4. Castañeda-Miranda, A.; Icaza-Herrera, M.; Castaño, V.M. Meteorological Temperature and Humidity Prediction from Fourier-Statistical Analysis of Hourly Data. Advances in Meteorology, 2019, 1-13, (2019).
5. Li-Li, G.; Yong, L.; Zi-Wei, L.; Hua-Wei, S. Application of Particle Swarm Optimization BP Algorithm in Air Humidity of Greenhouse Crops. IOP Conference Series: Materials Science and Engineering, 565, (2019).
6. Izzatdin, A.; Ismail, M.J.; Haron, N.; Mehat, M. Remote Monitoring Using Sensor in Greenhouse Agriculture. 2008 International Symposium on Information Technology, pp. 1-8, (2008).
7. Lu, Y.-S.; Lai, K.-Y. Deep-Learning-Based Power Generation Forecasting of Thermal Energy Conversion. Entropy, 22, 1161, (2020).
8. Jha, K.; Doshi, A.; Patel, P.; Manan, S. A comprehensive review on automation in agriculture using artificial intelligence. Artificial Intelligence in Agriculture, 2, 1-12, (2019).
9. Jung, D.H.; Kim, H.S.; Jhin, C.; Kim, H.J.; Park, S.H. Time-serial analysis of deep neural network models for prediction of climatic conditions inside a greenhouse. Computers and Electronics in Agriculture, 173, 2-11, (2020).
10. Hongkang, W.; Li, L.; Yong, W.; Fanjia, M.; Haihua, W.; Sigrimis, N. A., Recur-rent Neural Network Model for Prediction of Microclimate in Solar Greenhouse. IFAC-Papers Online, 51, 790–795, (2018).
11. Abdulkarim, S.A.; Engelbrecht, A.P. Time Series Forecasting Using Neural Networks: Are Recurrent Connections Necessary? Neural Processing Letters, 50, 2763-2795, (2019).
12. Wang, K.; Qi, X.; Lui, H. Deep belief network based k-means cluster approach for short-term wind power forecasting. Energy, 165, 840-852, (2018).
13. Zhang, X.; Zhang, G.; Nie, Z.;Gui, Z.; Que, H. A Novel Hybrid Data-Driven Model for Daily Land Surface Temperature Forecasting Using Long Short-Term Memory Neural Network Based on Ensemble Empirical Mode Decomposition. Int. J. Environ. Res. Public Health, 15, 1032, (2018).
14. Karevan, Z.; Suykens, J. Transductive LSTM for time-series prediction: Anapplication to weather forecasting. Neural Networks, 125, 1-9, (2020).
15. Tran, T.T.K.; Bateni, S.M.; Ki, S.J.; Vosoughifar, H. A Review of Neural Networks for Air Temperature Forecasting. Water, 13, 1294, (2021).
16. Singh, V.K.; Tiwati, K.N. Prediction of greenhouse microclimate using artificial neural network. Applied Ecology and Environmental Research, 15, 1, 767-778, (2017).
17. Nacimento, S.; Valdenegro-Toro, M. Modeling and Soft-fault Diagnosis of Under-water Thrusters with Recurrent Neural Networks. IFAC-PapersOnLine, 51, 29, 80–85, (2018).
18. Outanoute, M.; Lachhab, A.; Ed-Dahhak, A.; Selmani, A.; Guerbaoui, M.; Bouch-ikhi B. A neural network dynamic model for temperature and relative humidity control under greenhouse. 2015 Third International Workshop on RFID and Adaptive Wireless Sensor Networks (RAWSN), 6-11, (2015).
19. Ali, A.; Hassanein, H.S. Wireless Sensor Network and Deep Learning for Prediction Greenhouse Environments. International Conference on Smart Applications, Communications and Networking (SmartNets). 1-5, (2019).

20. Geng, D.; Zhang, H.; Wu, H. Short-Term Wind Speed Prediction Based on Principal Component Analysis and LSTM. Appl. Sci. 2020, 10, 4416, (2020).
21. Agana, N.A.; Homaifar, A. EMD-Based Predictive Deep Belief Network for Time Series Prediction: An Application to Drought Forecasting. Hydrology, 5, 18, (2018).
22. Pérez, I.; Godoy, A. Neural Networks-based models for greenhouse climate control. Actas de las XXXIX Jornadas de Automática, 875-879, (2018).
23. Hua Y.; Guo J.; Zhao H., Deep Belief Networks and deep learning, Proceedings of2015 International Conference on Intelligent Computing and Internet of Things, ICIT 2015, 1-4, (2015).
24. Klerkx L.; Jakku E.; Labarthe P., A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda, NJAS - Wageningen Journal of Life Sciences, 1573-5214, (2019).
25. Rose D.C.; Chilvers J., Agriculture 4.0: Broadening Responsible Innovation in an Era of Smart Farming, Front. Sustain. Food Syst., 1-7, (2018).
26. Lui Y.; Ma X.; Shu L.; Hancke G.P.; Abu-Mahfouz A. M., From Industry 4.0 to Agriculture 4.0: Current Status, Enabling Technologies, and Research Challenges, IEEE, 1-13, (2020).
27. Zhai Z.; Martínez J.F.; Beltrán V.; Martínez N. L., Decision support systems for agriculture 4.0: Survey and challenges, Computers and Electronics in Agriculture,1-16, (2020).
28. Raj M.; Gupta S.; Chamola V.; Elhence A.; Garg T.; Atiquzzaman M.; Niyato D.,A survey on the role of Internet of Things for adopting and promoting Agriculture4.0, Journal of Network and Computer Applications, 1-29, (2021).
29. Pspocsi L.; Csoto M.,Digital Excellence in Agriculture in Europe and Central Asia, Good practices in the field of digital agriculture Stocktaking Report, ITUand FAO,1-196, (2021)
30. Xue C.; Dongming L.;Limin S.;Zhenhui R., A virtual sensor simulation system of a flower greenhouse coupled with a new temperature microclimate model using three-dimensional CFD, Computers and Electronics in Agriculture, 1-14, (2021).
31. Singh V.K.; Tiwari K.N., Prediction Of Greenhouse Micro-Climate Using Artificial Neural Network, Applied ecology and environmental research, 767-778,(2017).
32. Xike Z.; Qiuwen Z.; Gui Z.; Zhiping N.; Zifan G.; Huafei Q., A Novel Hybrid Data-Driven Model for Daily Land Surface Temperature Forecasting Using Long Short-Term Memory Neural Network Based on Ensemble Empirical Mode De-composition, International Journal of Environmental Research and Public Health,1-23, (2018).
33. Hongkang W.; Li L.; Yong W.; Fanjia M.; Haihua W.; Sigrimis N., Recurrent Neural Network Model for Prediction of Microclimate in Solar Greenhouse, Science Direct, 790-795, (2018).